Science of the Total Environment 655 (2019) 1169–1180

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Carbon sinks and output of China's forestry sector: An ecological economic development perspective

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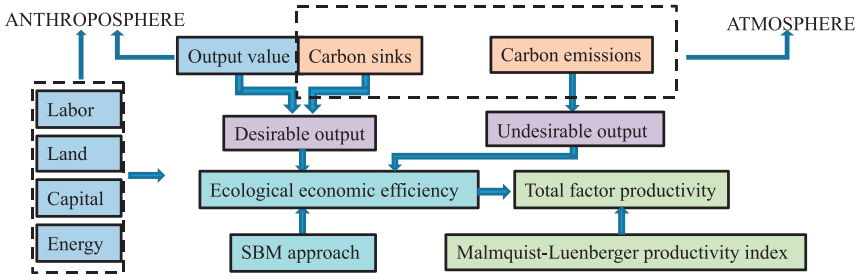
HIGHLIGHTS

- Forestry has a dual role in mitigating climate change and increasing output value.
- Atmosphere and anthroposphere are included to measure the forestry productivity.
- SBM approach and ML Index are used to explore forestry development.
- The forest ecological performance is better than the economic performance.
- Environmental factors have influence on total factor productivity of forestry.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 20 August 2018
Received in revised form 12 November 2018
Accepted 15 November 2018
Available online 19 November 2018

Editor: Elena Paoletti

Keywords:
Ecological-economic efficiency
Total factor productivity
Forest carbon sinks
Three-stage DEA

ABSTRACT

Forestry has a dual role in mitigating climate change and increasing regional output value. Therefore, forestry is meaningful for the anthroposphere and the atmosphere. In this study, slacks-based measure (SBM) approach and Malmquist–Luenberger Index are adopted to measure the static efficiency and dynamic changes in forestry productivity in thirty regions in China. Ecological development is measured by setting forest carbon sinks as desirable output and economic development is evaluated by forestry output value. Moreover, using the three-stage DEA model, the economic and environmental factors are introduced to adjust regional forest carbon sinks and forestry output slacks. Finally, from timely evolution and spatial non-equilibrium perspectives, the ecological-economic efficiency and total factor productivity of forests are analyzed according to the results. The results revealed that the estimators of ecological efficiency and productivity are greater than the economic development of the forest. The highest ecological economic efficiency and productivity is in the southwest region of China. Eight economic or environmental factors adjusting the output have influence on the total factor productivity of forestry, and the results show that harvest has no clear effect on environmental improvement. Policy implications are further proposed to develop environmental management to mitigate climate change.

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1. Introduction

Climate change characterized by global warming has attracted global attention. It has already had a major impact on the earth's ecosystem and thus has an impact on the socio-economic system. The main cause of climate warming is too much emissions of greenhouse gases and carbon dioxide emissions account for the largest share of greenhouse gases. Since *The United Nations Framework Convention on Climate Change* was proposed to stabilize greenhouse gases at a certain level, countries actively take relevant measures to reduce carbon emissions and develop carbon sequestration technologies which is mainly biological carbon sequestration. Forests play an important role in carbon dioxide fixation. The *Kyoto Protocol* put forward the Clean Development

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https://doi.org/10.1016/j.scitotenv.2018.11.219
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Mechanism and the concept of forest carbon sinks was first introduced. China joined the *Paris Agreement* in 2016 and assumed responsibility for controlling global greenhouse gas emissions. While reducing carbon emissions, China should also recognize the importance of forest carbon sequestration and focus on the development of forestry ecological construction in China to achieve its ecological benefits.

As a relatively complete industrial system, forestry is an important sector for realizing the dual goals of ecology and economy. It can reduce the CO_2 from the atmosphere and increase the output for anthroposphere, which mainly are woods. In particular, its strong carbon sequestration function plays a significant role in carbon emissions reduction to achieve energy conservation and emission reduction strategies (Makkonen et al., 2015; Pingoud et al., 2016; Pingoud et al., 2018). Gu et al. (2015) proposed an increase in carbon storage of Chinese forests attributed to increasing of nitrogen deposition during 1981–2010. Therefore, climate change mitigation can be achieved by investigating policy coherence in relation to ecosystem services, and forest ecosystem services in particular. The use of wood for energy production and the management of forests for carbon sequestration both rely on the functions of forested ecosystems (Makkonen et al., 2015). Sustainably managed commercial forests are important source of renewable bio-energy while simultaneously sequestering atmospheric carbon (Koponen et al., 2018).

Total Factor Productivity (TFP) is the portion of output not explained by the amount of inputs used in production. As such, its level is determined by how efficiently and intensely the inputs are utilized in production. TFP is a measure of economic efficiency (Hulten, 2001; Comin, 2008). Considering the forestry output value and carbon sinks, this study is aimed to explore the environment and economic performances of forestry by using indicators of total factor productivity, and to find timely evolution or spatial non-equilibrium of the forestry development. Therefore, this study sets the hypothesis that the outputs of forestry are output value and carbon sinks. Output value is represented the economic performance of forestry and carbon sink is its environment performance. The contributions of this study may be as follows: (1) In general, multiple undesirable outputs are measured by using DEA method. This study sets two desirable outputs and calculates the efficiency and TFP based on different desirable outputs. (2) This research tries to measuring total factor productivity of forest carbon sinks in China's different regions and conducting comparative analyses between different regions. (3) In the second stage of three-stage DEA method, two kinds of slack outputs are adjusted incorporating eight uncontrollable variables aimed to compare the effects of environmental and economic factors on forest productivity.

2. Literature review

Forests have the function of carbon sinks (Song et al., 2018) and it is an approach for managing carbon dioxide emission (Ray and Jana, 2017). Wang et al. (2007) reported the carbon sinks in China's forests and Deng et al. (2011) explored the economic values of carbon sink and carbon stock of forest system. The strategies of offsetting carbon emissions include scrubbing, fuel switching, investments in energy conservation and efficiency, and afforestation. Thus cost of carbon dioxide sequestered by afforestation is the lowest as seen in Dudek and LeBlanc (1990).

With consideration of forest's dual effects on climate change mitigation and wood production, Pingoud et al. (2018) proposed the trade-offs between harvested wood flows and forest carbon stocks. Strategies that keep the production level at Pareto-optimal should be taken. Forests can provide carbon sinks and bioenergy thereby whether forest carbon sequestration is worth increasing at the expense of biomass energy and wood production becomes an important policy decision (Adams et al., 1993; Vass and Elofsson, 2016). These mixed outputs should be considered when forest management policies are made (Makkonen et al., 2015). Furthermore, how to get social optimum levels of the size of climate cost and taxes or subsidies have been explored (Hoel and Sletten, 2016; Guo and Gong, 2017). Valade et al. (2017) think forest carbon sequestration should be sustained, but there is uncertainty about the response of forests to climate change in making optimal carbon management strategies. O'Mara (2012) emphasized the role of grasslands in food security and climate change. Land use type will affect terrestrial carbon sinks (Xu et al., 2016). Land use processes including afforestation, reforestation and deforestation have an impact on carbon sequestration and carbon sequestration policies are an important part of global climate change strategies (Lubowski et al., 2006; Rokityanskiy et al., 2007). Furthermore, land use change has influence on carbon sequestration cost. Some other critical factors such as natural management, deforestation regimes, prices and so on also affect it (Newell, 2000; Adetoye et al., 2018). Therefore, reforesting degraded lands is useful for mitigating atmospheric carbon emissions in developing countries (Niles et al., 2002; van Kooten et al., 1992). Rajashekar et al. (2018) suggested forest carbon is a key part of the global carbon cycle and the spatial distribution of forest carbon has an influence on carbon intensity among different forest regions. Williams et al. (2016) proposed that the harvest is the extensive disturbance of the forest carbon balance, and fire, wind-throw, bark beetles, droughts are also disturbances. Hadden and Grelle (2016) studied how temperature change affects the carbon sinks in carbon sources, and the results show that the functioning of the ecosystem has more influence than climate warming.

There are some existing studies on policy design for forest carbon sequestration (Richards, 2004; Gren and Zeleke, 2016). Although several articles present extensive analysis on forest carbon sinks, only few of them explores its productivity and efficiency. Therefore, this study tries to calculate the efficiency and total factors productivity of forest carbon sequestration in China, and analyzes the differences across China's different regions.

3. Methodology

Data Envelopment Analysis is the most commonly used method for efficiency measurement. The standard DEA models ignore undesirable outputs, but a growing literature has emerged that models consider overall production of both good and bad outputs while calculating efficiency (Chung et al., 1997; Färe and Grosskopf, 2004). It is widely applied to energy and environmental issues. Dakpo et al. (2016) reviewed the models integrating environmental factors, especially pollution, into measuring productivity and discussed the limits of each method. Sueyoshi et al. (2017) summarized 693 previous research articles which applied DEA models to energy and environmental issues. Mardani et al. (2017) made a comprehensive review about using DEA method to analyze energy efficiency. Some authors also used DEA method to analyze energy efficiency and energy savings potential in China (Lin and Du, 2013; Feng and Wang, 2017; Feng et al., 2018). And Lin and Du (2015) modeled the carbon emission performance in China by malmquist index. Vlontzos et al. (2014) attempted a non-radial DEA model to evaluate the energy and environment efficiency of the primary sectors of EU members by setting energy input and environment output. Further, Vlontzos and Pardalos (2017) implemented DEA Window method to assess greenhouse gas emissions efficiency which is the undesirable output. It can be found from the above literature that the DEA model can effectively measure energy and environmental efficiency, whether it is input-oriented or output-oriented. Zhang et al. (2011) used Malmquist-Luenberger productivity index to evaluate the total factor productivity of China's economic growth while incorporating undesirable outputs. Chen (2015) adopted SBM approach and Luenberger index to conduct the evaluation indicator of China's provinces considering different undesirable outputs. This study aims to measure efficiency and productivity change to analyze the economic performance and ecological performance of forestry industry by using DEA models. The models can explore the industry development from static and dynamic perspectives. Therefore, this paper mainly uses the SBM approach to measure efficiency scores and Malmquist-Luenberger index for calculation of productivity change.

Bai-Chen et al. (2012) used a two-stage DEA model to compare environmental performance of China's power system in thirty provinces.

Li and Lin (2016) analyzed the impact of energy conservation policies on productivity through three-stage DEA model with consideration of implementation and statistical noise. Four-stage DEA model is used to measure energy efficiency (Fang et al., 2013). Because both the environmental and economic factors and statistical noise will affect the evaluation of productivity, it is necessary to place all decision-making units (DMUs) in the same operating environment in order to re-evaluate productivity. Of the above methods, the three-stage DEA model can adjust the efficiency values by controlling some environmental and economic variables, and is suitable for measuring the effect of the variables on productivity. Therefore, this study adopts the three-stage DEA model to analyze the effects of environmental and economic factors on total factor productivity of forest carbon sink.

3.1. SBM approach

Tone (2011) proposed a slacks-based measure (SBM) of efficiency in DEA model and Chen (2015) measured environmental efficiency using the method. This study adopts the SBM method to calculate the ecological economic efficiency score in China's forestry system.

Assume there are k decision-making units (DMUs) at t time point. For each DMU, there are m desirable outputs, i undesirable outputs and n inputs. x, y, b, X, Y and B represent the column vector and matrix of inputs, desirable outputs and undesirable outputs, respectively. The production set P could be defined as:

$$\mathrm{P} = (x, y, b) \mid x \geq X, y \leq Y, b \geq B, \geq 0 \tag{1}$$

The efficiency score for ith DMU in terms of t-time observations could be obtained by resolving the following equation of SBM approach.

$$S^t\left(x_k^t, y_k^t, b_k^t\right) = \min \frac{1-\left(\frac{1}{n}\right)\sum_{n=1}^{n}\left(\frac{s_n^{x,-}}{x_{n,k}^t}\right)}{1+\left[\frac{1}{i+m}\right]\left[\sum_{m=1}^{m}\left(\frac{s_m^{y,+}}{x_{m,k}^t}\right)+\sum_{i=1}^{i}\left(\frac{s_i^{b,-}}{x_{i,k}^t}\right)\right]} \tag{2}$$

$$\mathrm{s.t.} x_k = X\lambda + s_{\mathrm{k}}^{x,-} \tag{3}$$

$$y_k = Y\lambda + s_{\mathrm{k}}^{y,+} \tag{4}$$

$$b_k = B\lambda + s_{\mathrm{k}}^{b,-} \tag{5}$$

$$s_{\mathrm{k}}^{x,-} \geq 0 \tag{6}$$

$$s_{\mathrm{k}}^{y,+} \geq 0 \tag{7}$$

$$s_{\mathrm{k}}^{b,-} \geq 0 \tag{8}$$

$$i'\lambda = 1 \tag{9}$$

$$\lambda \geq 0 \tag{10}$$

where $s_{\mathrm{k}}^{x,-}$, $s_{\mathrm{k}}^{y,+}$ and $s_{\mathrm{k}}^{b,-}$ are slack variables which represent the over-inputs, under-desirable outputs and over-undesirable outputs. λ is the intensity vector, the summation of its elements being 1 since it assumes varying returns to scale. The efficiency score lies between 0 and 1, and the larger the score, the higher the efficiency of the DMU. If $S^t(x_k^t, y_k^t, b_k^t) = 1$, the DMU is efficient.

3.2. Directional distance functions

According to Chung et al. (1997) and Zhang et al. (2011), the original Malmquist index uses Shephard output distance functions to represent technology. The Shephard output distance function increases the good and bad outputs simultaneously. In contrast, the directional distance function changes the good and bad outputs with the given direction and it is possible to increase the good outputs while decreasing the bad ones. It is defined as:

$$\overrightarrow{D_0}\left(x, y, b; \vec{g}\right) = \max\left\{\beta : \left(x-\beta\vec{g}, y+\beta\vec{g}, b-\beta\vec{g}\right)\right\} \tag{11}$$

The directional distance functions can be calculated as the solutions to linear programming problems. For instance, for observation k′ at period t:

$$\overrightarrow{D_0}^t\left(x^{t,k'}, y^{t,k'}, b^{t,k'}; y^{t,k'}, -b^{t,k'}\right) = \max\beta \tag{12}$$

$$\mathrm{s.t.} \sum_{k=1}^{K} z_k^t y_{mk}^t \geq (1+\beta) y_{mk'}^t, \mathrm{m} = 1, \ldots, \mathrm{M} \tag{13}$$

$$\sum_{k=1}^{K} z_k^t b_{ik}^t \leq (1-\beta) b_{ik'}^t, \mathrm{i} = 1, \ldots, \mathrm{I} \tag{14}$$

$$\sum_{k=1}^{K} z_k^t x_{nk}^t \leq x_{nk'}^t, \mathrm{n} = 1, \ldots, \mathrm{N} \tag{15}$$

$$z_k^t \geq 0, k = 1, \ldots, K \tag{16}$$

And the other linear programming problem should be solved. It is the directional distance function for observation k′ at period t + 1 with using period t technology:

$$\overrightarrow{D_0}^t\left(x^{t+1,k'}, y^{t+1,k'}, b^{t+1,k'}; y^{t+1,k'}, -b^{t+1,k'}\right) = \max\beta \tag{17}$$

$$\mathrm{s.t.} \sum_{k=1}^{K} z_k^t y_{mk}^t \geq (1+\beta) y_{mk'}^{t+1}, \mathrm{m} = 1, \ldots, \mathrm{M} \tag{18}$$

$$\sum_{k=1}^{K} z_k^t b_{ik}^t \leq (1-\beta) b_{ik'}^{t+1}, \mathrm{i} = 1, \ldots, \mathrm{I} \tag{19}$$

$$\sum_{k=1}^{K} z_k^t x_{nk}^t \leq x_{nk'}^{t+1}, \mathrm{n} = 1, \ldots, \mathrm{N} \tag{20}$$

$$z_k^t \geq 0, k = 1, \ldots, K \tag{21}$$

3.3. Malmquist–Luenberger index

The ML productivity indices are constructed with directional distance functions in a similar way to the traditional Malmquist indices which are formulated from Shephard distance functions. Following Chung et al. (1997), the ML productivity index between time t and t + 1 can be defined as:

$$ML_t^{t+1} = \left[\frac{\left(1+\overrightarrow{D_0}^{t+1}\left(x^t, y^t, b^t; y^t, -b^t\right)\right)}{\left(1+\overrightarrow{D_0}^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)\right)} * \frac{\left(1+\overrightarrow{D_0}^{t}\left(x^t, y^t, b^t; y^t, -b^t\right)\right)}{\left(1+\overrightarrow{D_0}^{t}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)\right)}\right]^{1/2} \tag{22}$$

An improvement in productivity is signaled by $ML_t^{t+1} > 1$ and a decrease in productivity by $ML_t^{t+1} < 1$.

3.4. Three-stage DEA

Total factor productivity is influenced by environmental factors, management inefficiencies and statistical noise resulting from measurement errors. The three-stage DEA model evaluates the green productivity which only results from difference in management. Therefore, it should eliminate the effects of uncontrollable variables and statistical noise (Fried et al., 2002; Zhang et al., 2011; Li and Lin, 2016). The steps are as follows:

3.4.1. Stage 1

The initial total factor productivity is conducted using the ML index, which uses input variables, desirable and undesirable outputs data.

3.4.2. Stage 2

In order to eliminate the effects of environmental influences and statistical noise among all DMUs, the stochastic frontier analysis (SFA) models are adopted to obtain the output slacks. Outputs can be adjusted by output slacks. Then all DMUs are in a common environment to measure their ML index which is only reflected by the management level.

Firstly, two different SFA regressions on desirable and undesirable outputs should be calculated to obtain output slacks (Zhang et al., 2011; Li and Lin, 2016). For the mth desirable output:

$$S_{kt}^m = f^m + v_{kt}^m + u_{kt}^m = \alpha_k^m + \beta^{m'}\lambda_{kt} + v_{kt}^m + u_{kt}^m \tag{23}$$

$$S_k^m = \sum_{k=1}^{K} z_k y_{mk} - y_{mk} \tag{24}$$

$$v_{kt}^m \sim \mathrm{N}\left(0, \sigma_{\mathrm{vm}}^2\right)$$

$$u_{kt}^m = \left|U_{kt}^m\right|, U_{kt}^m \sim \mathrm{N}\left(0, \sigma_{\mathrm{um}}^2\right) \perp v_{kt}^m$$

$$m = 1, \ldots, M; k = 1, \ldots, \mathrm{K}; t = 1, \ldots, \mathrm{T}$$

For the ith undesirable output:

$$S_{kt}^i = f^i + v_{kt}^i + u_{kt}^i = \alpha_k^i + \beta^{i'}\lambda_{kt} + v_{kt}^i + u_{kt}^i \tag{25}$$

$$S_k^i = b_{ik} - \sum_{k=1}^{K} z_k b_{jk} \tag{26}$$

$$v_{kt}^i \sim \mathrm{N}\left(0, \sigma_{\mathrm{vi}}^2\right)$$

$$u_{kt}^i = \left|U_{kt}^i\right|, U_{kt}^i \sim \mathrm{N}\left(0, \sigma_{\mathrm{ui}}^2\right) \perp v_{kt}^i$$

$$i = 1, \ldots, I; k = 1, \ldots, \mathrm{K}; t = 1, \ldots, \mathrm{T}$$

where S_{kt}^m and S_{kt}^i are the mth desirable output slacks and i$^{\mathrm{th}}$ undesirable output slacks of the kth DMU at the time t. f^m and f^i represents the effects of uncontrollable variables on the output slacks, and λ is the elements of the uncontrollable variables; $\beta^{m'}$ and $\beta^{i'}$ are the coefficients to be estimated; α_k^m, α_k^i measure the heterogeneity among the different DMUs. The v_{kt}^m is statistical noise and $u_{kt}^m \geq 0$ implies managerial inefficiency. $v_{kt}^m + u_{kt}^m$ are the composed error. v_{kt}^i, u_{kt}^i are the same as v_{kt}^m, u_{kt}^m. Similar to Li and Lin (2016), the true fixed effects stochastic frontier model is adopted in this model which was first proposed by Greene (2005). The reason is that the model can distinguish the inefficiency and heterogeneity though the conventional models may regard the heterogeneity as the inefficiency which makes efficiency is underestimated.

Secondly, outputs are adjusted by using output slacks. Two extreme situations are assumed. One is the luckiest situation which is the expected outputs are adjusted to the highest level and unexpected outputs are reduced to the lowest. The equations are:

$$\begin{aligned}\left(y_k^m\right)^A &= y_k^m + \left[\widehat{f_{k'}^m} - \min_k \widehat{f_k^m}\right] + \left[\widehat{v_{k't}^m} - \min_k \widehat{v_{kt}^m}\right] \\ &= y_k^m + \left[\left(\alpha_{k'}^m + \beta^{m'}\lambda_{k't}\right) - \min_k\left(\alpha_k^m + \beta^{m'}\lambda_{kt}\right)\right] \\ &\quad + \left[\widehat{v_{k't}^m} - \min_k \widehat{v_{kt}^m}\right], \\ &\quad k = 1, \ldots, K\end{aligned} \tag{27}$$

$$\begin{aligned}\left(b_k^i\right)^A &= b_k^i - \left[\widehat{f_{k'}^i} - \min_k \widehat{f_k^i}\right] - \left[\widehat{v_{k't}^i} - \min_k \widehat{v_{kt}^i}\right] \\ &= b_k^i - \left[\left(\alpha_{k'}^m + \beta^{m'}\lambda_{k't}\right) - \min_k\left(\alpha_k^m + \beta^{m'}\lambda_{kt}\right)\right] \\ &\quad - \left[\widehat{v_{k't}^i} - \min_k \widehat{v_{kt}^i}\right], \\ &\quad k = 1, \ldots, K\end{aligned} \tag{28}$$

The other one is unluckiest situation which is the expected and unexpected outputs adjusted are contrary to that of the luckiest situation, and the equations are:

$$\begin{aligned}\left(y_k^m\right)^A &= y_k^m - \left[\max_k \widehat{f_k^m} - \widehat{f_{k'}^m}\right] - \left[\max_k \widehat{v_{kt}^m} - \widehat{v_{k't}^m}\right] \\ &= y_k^m - \left[\max_k\left(\alpha_k^m + \beta^{m'}\lambda_{kt}\right) - \left(\alpha_{k'}^m + \beta^{m'}\lambda_{k't}\right)\right] \\ &\quad - \left[\max_k \widehat{v_{kt}^m} - \widehat{v_{k't}^m}\right], \\ &\quad k = 1, \ldots, K\end{aligned} \tag{29}$$

$$\begin{aligned}\left(b_k^i\right)^A &= b_k^i + \left[\max_k \widehat{f_k^i} - \widehat{f_{k'}^i}\right] + \left[\max_k \widehat{v_{kt}^i} - \widehat{v_{k't}^i}\right] \\ &= b_k^i + \left[\max_k\left(\alpha_k^m + \beta^{m'}\lambda_{kt}\right) - \left(\alpha_{k'}^m + \beta^{m'}\lambda_{k't}\right)\right] \\ &\quad + \left[\max_k \widehat{v_{kt}^i} - \widehat{v_{k't}^i}\right], \\ &\quad k = 1, \ldots, K\end{aligned} \tag{30}$$

where $\left(y_k^m\right)^A$ and y_k^m are observed and adjusted quantities of the kth DMU of the m$^{\mathrm{th}}$ desirable output, respectively; $\left(b_k^i\right)^A$ and b_k^i are observed and adjusted quantities of the kth DMU of the ith undesirable output, respectively.

In this stage, some environmental variables are introduced to obtain output slacks through SFA models and initial output variables are adjusted.

3.4.3. Stage 3

The new values of the TFP are re-computed with input variables which are used in Stage 1 and the adjusted output variables which are obtained from Stage 2. The effects of environmental variables can be obtained by comparing ML indexes in Stage 1 and Stage 3.

4. Variables and data

4.1. Input and output variables

4.1.1. Inputs

Input variables include forest land, forestry labor, capital stock and energy consumption. Labor, capital stock and energy are conventional inputs to calculate efficiency. Forest land is also a key input for forestry development. Hence these four input variables are selected in this paper.

The data source of forestry land and labor is from *China Forestry Statistical Yearbook*. Capital stock has no statistical data and is calculated according to the perpetual inventory method (Chen, 2015). The source of fixed asset investment data is *China Forestry Statistical Yearbook*. There is no direct data source for energy consumption (coal, oil, natural gas) in

forestry production. Since there is no differentiation in the statistical data for agriculture, forestry, animal husbandry and fishery, the energy consumption of forestry is mainly due to large-scale machinery, harvesting and fertilization. The materials and structures of production in the four industries: agriculture, forestry, animal husbandry and fishery are similar. Therefore, the ratio of forestry output value to the total output value of these four industries is used to calculate the energy consumption of forestry from the four industries.

4.1.2. Outputs

The outputs of this study include two expected outputs of forestry output value and carbon sinks. Carbon dioxide emissions from the forestry production process is the undesirable output.

The forest carbon sinks volume is the forest carbon stocks in current year minus that of the previous year. According to the calculation formula of the bio-carbon reserves in the IPCC2006 report, forest carbon stocks in China's 30 provinces (except Tibet)[1] can be estimated as follows:

$$C = A * V * BEF * D * (1 + \mathrm{R}) * (1 + \mathrm{RDW}) * CF \quad (31)$$

In the above equation, A is the area of land remaining in the same land-use category (Unit: ha), V is merchantable growing stock volume (Unit: m^3/ha), A * V represents the total stock volume of the forest. R is the ratio of below-ground biomass to above-ground biomass. RDW represents ratio of life and death, CF is the carbon fraction of dry matter. BEF is biomass expansion factor, and D is the basic wood densities. The forest stock data in China was obtained from the *China Forestry Statistical Yearbook*. Values of the other parameters are based on the *2015 Global Forest Resources Assessment China Report*. All the parameters are calculated by weighted average in this paper since the parameters of different tree species are different. Table 1 shows the specific values of the parameters.

The forestry output value data was obtained from *China Statistical Yearbook*. The undesirable output is the amount of carbon dioxide emissions during forestry production. The calculation of carbon dioxide emissions is based on Chen (2015). Due to the incomplete statistics of forest resources in all regions before 2003, all indicator data of this study range from 2003 to 2016.

4.2. Uncontrollable environment variables

In stage 2 of the three-stage DEA model, the influence of environment variables should be excluded. Hence this article introduces some factors which may have an effect on the forest carbon sinks and output value of forestry.

4.2.1. Case 1: forest carbon sinks and carbon emissions slacks

(1) Harvest (HAR). It is measured by the proportion of the total amount of timber, farmers and firewood harvest to the forest volume (unit: %). The data was obtained from *China Forestry Statistical Yearbook*. Harvest plays an important role in the forming of carbon sinks or carbon source of forest, and more carbon emissions will be produced when there is more harvest (Williams et al., 2016; Valade et al., 2017).
(2) Rate of forest disease prevention (RFDP). It is measured by the proportion of the total area of forest disease prevention to forest area in all regions. The data was also obtained from *China Forestry Statistical Yearbook*. Forest diseases will affect the growth of trees, which will affect the amount of forest reserves in different regions (Williams et al., 2016).
(3) Forest coverage (FC). The data on forest coverage and cultivated area is from *National Bureau of Statistics*. Changes in land use have a significant impact on the formation of forest carbon sinks or carbon sources. Xu et al. (2016) proposed complex changes in carbon sources and sinks caused by rapid urbanization have been observed with land use changes in quantity, structure and spatial pattern. Song et al. (2018) suggested that the potential carbon dioxide consumption rate of forests is influenced by the combined action of afforestation and reforestation.
(4) Forestry research and development (RD). This is according to the number of persons engaged in research and development in different regions. The data was obtained from *China Forestry Statistical Yearbook*.

[1] There is missing data in Tibet, so this study does not evaluate Tibet.

Table 1
The parameters value in the equation of carbon sinks estimation.

Parameters	Value
BEF	1.3539
D	0.43
R	0.3789
CF	0.47
RDW	0.1727

Note:
R: the ratio of below-ground biomass to above-ground biomass.
RDW: the ratio of life and death.
CF: the carbon fraction of dry matter.
BEF: biomass expansion factor.
D: the basic wood densities.

4.2.2. Case 2: forestry output value and carbon emissions slacks

(1) Land use structure (LUS). It is measured by the proportion of the cultivated area to the forest area (unit: %). The data on forest area and the cultivated area were sourced from *China Forestry Statistical Yearbook*. Changes in land use can have an impact on forest carbon sinks and also affect forestry output value. Timber harvest is also a kind of forest output value.
(2) Output value structure (OVS). It is measured by the proportion of primary industry output value of forestry to output value of forestry (unit: %), and the data was obtained from *China Forestry Statistical Yearbook*.
(3) Energy use structure (EUS). Following Li and Lin (2016), this refers to the proportion of coal in the primary energy use and is measured in percentage (%). Energy consumption is the measured quantity of each fuel (coal, oil, and natural gas) by 10,000 tce according to the conversion factors from physical unit of each fuel to coal equivalent.
(4) Pollution governance investment intensity (PGI). It is measured by the proportion of pollution control investment in the total investment in the regions (unit: %), and the data was obtained from *Wind* database.

5. Results

The SBM method can be used to measure the static efficiency of forestry in the different regions of China. In the calculation of static efficiency, the scores based on forestry output value and forest carbon sink are defined as the ecological-economic efficiency. The efficiency scores can be defined as the economic efficiency based on forestry output value, and ecological efficiency is the score based on forest carbon sinks. The Malmquist–Luenberger index is a measurement of the total factor productivity of forestry in all regions including the expected forestry output value and forest carbon sinks, and undesirable output of carbon emissions. Total factor productivity is a dynamic measurement. This paper measures the ecological economic development in China's forestry from both static and dynamic aspects.

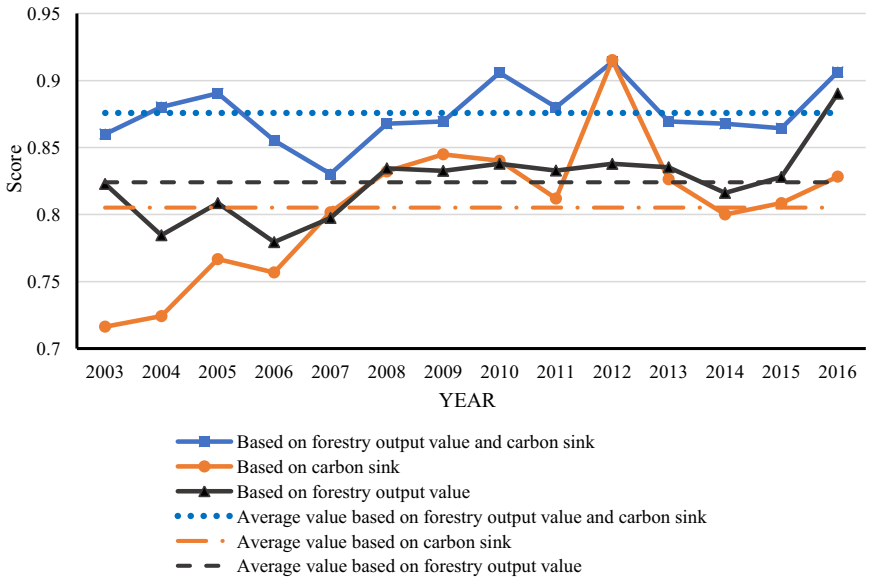
0.95
0.9
0.85
0.8
0.75
0.7
Score
2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016
YEAR
Based on forestry output value and carbon sink
Based on carbon sink
Based on forestry output value
Average value based on forestry output value and carbon sink
Average value based on carbon sink
Average value based on forestry output value

Fig. 1. Average efficiency scores of all the regions in China. Note: The scores are between 0 and 1. There are three kinds of measurements of the efficiency scores which outputs are based on forestry output value, carbon sink and both of them.

5.1. Results of SBM

5.1.1. Timely evolution

Fig. 1 shows the efficiency of China's forestry sector based on the SBM approach from 2003 to 2016. The measurement results are in the range of 0.7 to 0.95. Annual average values of efficiency based on both output value and carbon sinks variables, only carbon sinks and only output value are 0.8758, 0.8053 and 0.8242 respectively. It can be seen from Fig. 1 that the efficiency based on both output value and carbon sinks are basically around the annual average value, and there is no obvious upward or downward trend. The efficiency based on only carbon sinks and only output value present a similar changing trend. However, efficiency based on forest carbon sinks have a clear trend, and it has been almost increasing until 2012. The efficiency of carbon sinks has reached its highest level in 2012, and then gradually declined until 2014, before it started showing an upward development afterward.

5.1.2. Regional difference

Based on the calculation of forestry static efficiency from 2003 to 2016, the standard deviation and coefficient of variation are used to calculate the differences in forestry production efficiency in the 30 regions in China. The results are shown in Fig. 2. The standard deviation represents the absolute difference in the production efficiency of forest between different regions. The standard deviations in all the years are between 0.15 and 0.35. The coefficient of variation represents the relative difference in efficiency between provinces or cities, and the results of the coefficient of variation are concentrated between 0.15 and 0.45. From Fig. 2, the trends of relative and absolute differences were almost identical. Similar to the results of changes in the time-series, the eco-economic efficiency and economic efficiency of forestry had almost the same difference in regional trend. Ecological efficiency based on forest carbon sinks in forestry had bigger difference in the 30 provinces than economic efficiency, and it generally showed a downward trend year by year. In 2012, the absolute and relative regional differences were smallest. The standard deviation and the coefficient of variation were small, therefore the regional differences were not obvious.

5.1.3. Provincial efficiency

Table 2 shows the average eco-economic efficiency scores from 2003 to 2016 based on the SBM approach. And different output variables are into calculation. Seven geographical regions are divided according to Chinese Geographical Division,[2] and 30 provinces and cities are divided for better comparative analysis of ecological and economic efficiency.

From the perspective of the annual average results, the ecological efficiency of China's forest carbon sinks is relatively low, which is lower than the economic efficiency based on forestry output value. From the average of the efficiency scores of the seven regions, it can be found that the highest ecological efficiency score and the economic score are in southern China, and the highest ecological efficiency score is in southwest China. The lowest three efficiency score is in northern China. Based on the results of the provincial eco-economic static efficiency analysis, Beijing, Guangdong, Guangxi, Hainan, Heilongjiang, Henan, Jiangsu, Jiangxi, Jilin, Ningxia, Qinghai, Shandong, Shanghai, Yunnan, and Zhejiang had an efficiency score of 1. The results of eco-efficiency calculation based on carbon sinks showed Beijing, Guangxi, Jiangsu, Qinghai, Shanghai, Yunnan, Beijing, Guangdong, Guangxi, and Hainan had higher scores, and the highest input-output efficiency scores based on forestry output value are in Jiangsu, Qinghai, Shanghai and Zhejiang.

5.2. Results of ML index

5.2.1. The first stage

From the timely evolution perspective, the changes in total factor productivity of forestry by ML index in China from 2003 to 2016 are shown in Fig. 3. This includes the results of total factor productivity based on forestry output value, forest carbon sinks and both of them. ML index >1 represents an increase in productivity, and a value <1 represents a decrease. From Fig. 3, it can be seen that the total factor productivity of China's forest carbon sinks almost fluctuated around 1. The increase in total factor productivity based on forestry output value and forest carbon sink were from 2006 to 2007 and from 2010 to 2015. The periods of increase in total factor productivity based on forest carbon sinks were 2006–2007 and 2010–2016. From 2011 to 2012, the total factor productivity of forest carbon sinks increased significantly.

[2] They are the Northeast (Heilongjiang, Jilin and Liaoning province), East China (Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi and Shandong province), North China (Beijing, Tianjin, Shanxi, Hebei and Inner Mongolia province), Central China (Henan, Hubei and Hunan province); South China (Guangdong, Guangxi and Hainan province), Southwest (Chongqing, Sichuan, Guizhou and Yunnan province) and the last region is Northwest (Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang province).

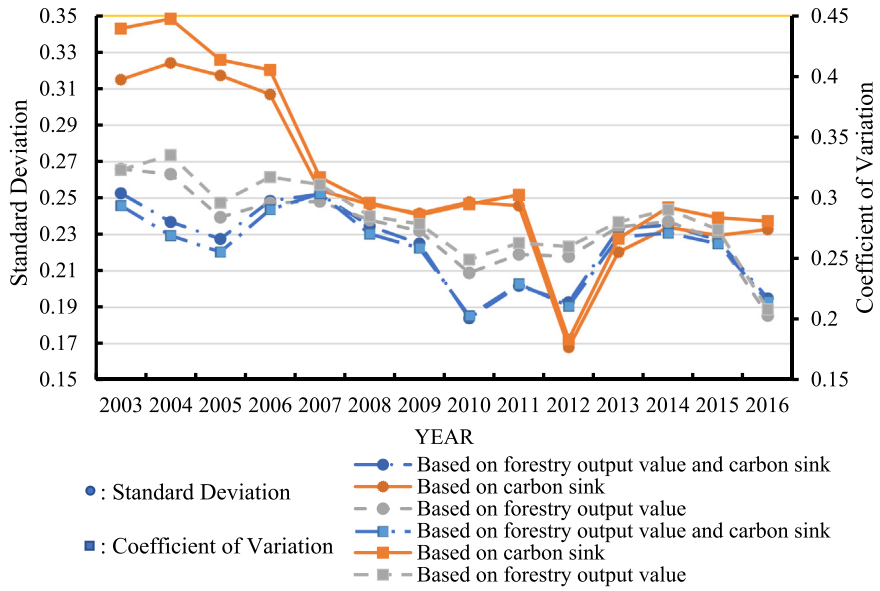
Standard Deviation
Coefficient of Variation
YEAR
2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016
: Standard Deviation
: Coefficient of Variation
Based on forestry output value and carbon sink
Based on carbon sink
Based on forestry output value
Based on forestry output value and carbon sink
Based on carbon sink
Based on forestry output value

Fig. 2. The standard deviation and coefficient of variation of efficiency scores. Note: The standard deviation and coefficient of variation are calculated by the efficiency scores estimation of China's thirty regions in one year. The efficiency scores are estimated by which outputs are based on forestry output value, carbon sink and both of them. And the lines are about the timely trend of them from 2003 to 2016.

The trend of total factor productivity based on forestry output values increased over the period 2006–2007 and 2010–2013, and the productivity declined in other years. The average total factor productivity of the three indexes over 2003–2016 is 0.9906, 1.0136 and 0.9875 respectively. Therefore, only the total factor productivity of forest carbon sinks is >1, followed by total factor productivity based on carbon sink and output value. The smallest is the productivity of forestry output value.

Table 3 shows the average ML index of forestry production in different regions of China from 2003 to 2016. This reflects the dynamic changes in total factor productivity in each region. Overall, total factor productivity increased by 1.36% while considering only carbon sinks. On the other hand, productivity fell by 1.25% while considering forestry output value. From the perspective of the seven geographical regions in China, the average total factor productivities of carbon sinks in the seven regions were >1. The total factor productivity of forestry output value was >1 only in Northern China, and the productivities of the other regions declined.

5.2.2. The second stage: SFA models

In the second stage, the fixed-effect stochastic frontier model is used to test the impact of environmental and economic factors on the outputs slacks. With carbon sinks and carbon emissions slack, the environmental variables introduced are harvest, rate of forest disease prevention, forest coverage and forestry research and development. Under the scenario of forestry output value and carbon emissions slack, the variables introduced are land use structure, output value structure, energy use structure and pollution governance investment intensity.

Tables 4 and 5 summarize the regression results of the fixed-effect stochastic frontier models. The limitation is that it cannot distinguish between management inefficiency u_{kt} and statistical errors v_{kt}. λ represents σ_{um}/σ_{vm}. It means that there is a large difference in management efficiency between regions according to the regression results. Therefore, the fixed-effect stochastic frontier model is applicable to the regional output adjustment.

5.2.3. The third stage: incorporating uncontrollable environmental and economic variables in ML index

Based on the results of the second stage (fixed-effect stochastic frontier model), the outputs of the two extreme situations under the output slacks conditions are adjusted. According to the adjusted outputs, the total factor productivities of forestry in China are re-calculated. The calculation results are shown in Table 6.

First, with forestry carbon sinks and carbon emissions being slack, the average ML index in the different regions of China is 1.0059 if environmental regulations were most ineffective. When environmental regulations are more stringent, the ML index of forestry in each province or city is relatively limited at 1.2007. Therefore, total factor productivity fell by 19.5% when comparing a state of ineffective environmental management with strict implementation of environmental regulations.

The second is the adjustment of forestry output value and carbon emissions. The average total factor productivity of forestry in China is 1.0013 if environmental regulations are ineffective and 1.0209 if there is strict environmental control. By comparing the total factor productivity under the two types of outputs slacks, it can be seen that total factor productivities are all higher with strict environmental regulations which is the luckiest situation.

6. Discussion

The results of SBM approach can be used to explain the static efficiency, ML index can be understood about the dynamic productivity of forestry. Therefore, the results will be discussed from static and dynamic points of view. And this paper defines eco-economic efficiency or productivity based on both two desirable output variables. Ecological performance is represented based on forest carbon sinks and economic performance is based on forestry output value.

6.1. Trend analysis

From the results of static efficiency, ecological efficiency had a clear upward and downward trend. The production efficiency of forest carbon sinks reached its highest level in 2012 and declined gradually until 2014. Then there was an upward trend from 2014 to 2016. Average eco-efficiency based on carbon sinks was lower than the economic efficiency based on forestry output value, and eco-efficiency was significantly higher than economic efficiency in 2012. Since a large part of the inputs is invested in the production process of forestry output value, the efficiency of forest carbon sinks based on forestry as the carrier will be underestimated. Followed by the dynamic changes from

Table 2
The result of efficiency scores[a].

Region	Output		
	Forestry output value and carbon sink	Carbon sink	Forestry output value
Anhui	0.9703	0.7073	0.9776
Beijing	1	1	1
Chongqing	0.9343	0.9104	0.7597
Fujian	0.9532	0.9228	0.9197
Gansu	0.5569	0.5885	0.5321
Guangdong	1	0.9039	1
Guangxi	1	1	1
Guizhou	0.7960	0.8581	0.5731
Hainan	1	0.4603	1
Hebei	0.8814	0.7080	0.9034
Heilongjiang	1	0.9178	0.9388
Henan	1	0.7413	0.9846
Hubei	0.638	0.6976	0.5757
Hunan	0.7088	0.7434	0.6152
Inner Mongolia	0.5383	0.7044	0.4397
Jiangsu	1	1	1
Jiangxi	1	0.8043	0.9936
Jilin	1	0.9695	0.9774
Liaoning	0.6669	0.5000	0.6871
Ningxia	1	0.9182	0.9869
Qinghai	1	1	1
Shaanxi	0.9352	0.7181	0.8126
Shandong	1	0.7774	0.9403
Shanghai	1	1	1
Shanxi	0.5847	0.4972	0.4086
Sichuan	0.9443	0.9433	0.8158
Tianjin	0.7162	0.5936	0.5582
Xinjiang	0.4495	0.6317	0.4449
Yunnan	1	1	0.8804
Zhejiang	1	0.9409	1
East China	0.9891	0.8789	0.9759
Central of China	0.7823	0.7275	0.7251
Southern China	1	0.7881	1
North China	0.7441	0.7006	0.6620
Northeast China	0.8890	0.7958	0.8678
Northwestern District of China	0.7883	0.7713	0.7553
Southwest of China	0.9187	0.9279	0.7573
Average	0.8758	0.8053	0.8242

[a] Efficiency scores of forestry are calculated by slacks-based measure (SBM). There are three kinds of output into calculation which are forestry output value, carbon sinks and both of them.

the results of total factor productivity, three output variables combinations are >1 from 2006 to 2007 and from 2010 to 2013. Productivity during these periods increased. In addition, annual total factor productivities of carbon sinks were larger than 1 in most years, and its average value is the largest. It indicates that the forestry ecological performance has witnessed an upward trend.

China began to gradually realize the importance of the construction of ecological civilization. It was first introduced in the CPC (Communist Party of China) Central Committee and State Council Meeting on accelerating the development of forestry in 2003. The construction of ecological civilization had been further improved since it was incorporated into the 18th report of the Communist Party of China in 2012. Provinces and cities implemented policies including subsidies for afforestation, returning farmland to forests and so on, with the aim of promoting the growth rate of forest reserves. Hence, it showed the increase in total factor productivity based on forest carbon sinks. In this process, the output of timber production had been reduced and the output of forest carbon sinks increased at the same time. As a result, ecological efficiency would increase and surpass economic efficiency.

6.2. Spatial non-equilibrium analysis

The differences among the 30 regions in China were small according to the result of the relative and absolute differences. However, there is spatial non-equilibrium existing. According to the results of forest carbon stocks, they are relatively larger in Yunnan, Inner Mongolia, Fujian, Guangxi, Sichuan, Heilongjiang, Jiangxi, and Guizhou. Although forest carbon sinks are abundant in these areas, ecological efficiencies are low in some regions according to SBM results. On the contrary, forest carbon sinks in Beijing, Shanghai, and Jiangsu have higher efficiency. The production efficiencies of all the industries are relatively high in Beijing and Shanghai which have rapid economic development. Forestry is not a key industry for economic development and the inputs of forestry production are lower. It may cause higher production efficiencies. Based on the economic performance, Beijing, Guangdong, Guangxi, Hainan, Jiangsu, Qinghai, Shanghai, and Zhejiang have higher efficiency. According to the *China Forestry Development Report*, the total forestry output value in the eastern region accounts for the largest proportion in China, and forestry output values in Guangdong, Shandong, Fujian, Jiangsu, Guangxi, and Zhejiang were higher.

From the results of ML index, the total factor productivities of carbon sinks in most provinces are increasing. The total factor productivities of

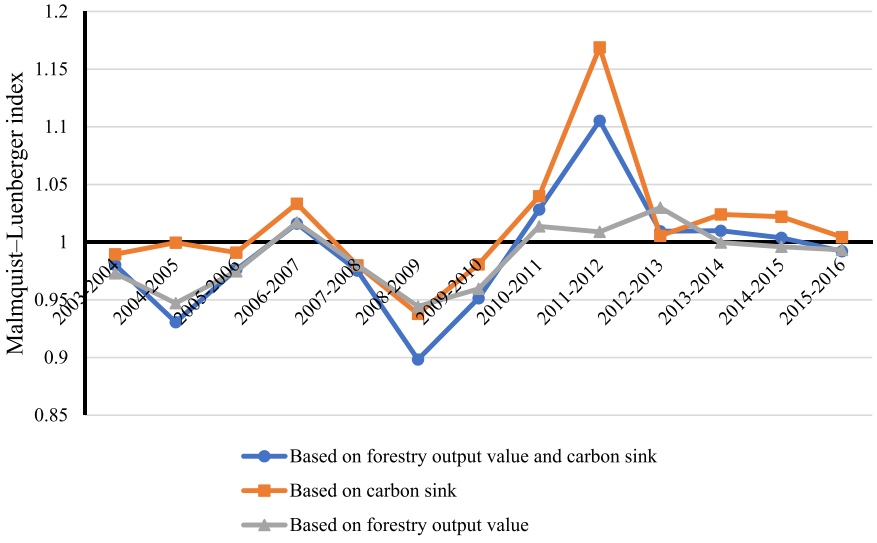

Fig. 3. The Malmquist–Luenberger index of China's forestry. Note: The result of Malmquist–Luenberger index can represent the dynamic total factor productivity which is the portion of output not explained by the amount of inputs used in production. When the index is larger than 1, there is an improvement productivity. When it is smaller than 1, there is a decrease in productivity. There are three kinds of calculations of the index which outputs are based on forestry output value, carbon sink and both of them.

Table 3
The result of Malmquist–Luenberger index.

Region	Output		
	Forestry output value and carbon sink	Carbon sink	Forestry output value
Anhui	*0.9508* (*27*)	1.0055 (19)	*0.9818* (*21*)
Beijing	1.0371 (3)	1.044 (4)	1.0371 (1)
Chongqing	1.0548 (1)	1.059 (1)	1.006 (3)
Fujian	*0.9768* (*21*)	*0.9988* (*24*)	*0.9902* (*10*)
Gansu	*0.9968* (*17*)	1.006 (18)	*0.9885* (*12*)
Guangdong	1.002 (11)	1.0055 (19)	*0.981 (22)*
Guangxi	*0.9339* (*28*)	*0.9777* (*28*)	*0.9802* (*24*)
Guizhou	1.0132 (7)	1.0132 (14)	1.0247 (2)
Hainan	*0.9821* (*20*)	1.0489 (2)	*0.995* (*6*)
Hebei	*0.9636* (*26*)	1.0266 (10)	*0.996* (*5*)
Heilongjiang	*0.9674* (*25*)	1.0034 (23)	*0.971* (*28*)
Henan	*0.9117* (*29*)	1.0401 (7)	*0.9872* (*13*)
Hubei	1.0017 (12)	1.0153 (13)	*0.9832* (*18*)
Hunan	*0.9715* (*23*)	*0.9621* (*30*)	*0.9459* (*30*)
Inner Mongolia	1.0053 (8)	1.0063 (17)	*0.9897* (*11*)
Jiangsu	*0.9734* (*22*)	1.0073 (16)	*0.9929* (*7*)
Jiangxi	*0.9071* (*30*)	*0.9807* (*27*)	*0.9794* (*25*)
Jilin	1.0007 (13)	1.0049 (21)	*0.9753* (*27*)
Liaoning	*0.9998* (*14*)	1.0196 (11)	*0.9854* (*17*)
Ningxia	*0.9708* (*24*)	1.0437 (5)	*0.9692* (*29*)
Qinghai	*0.9984* (*15*)	*0.9904* (*25*)	*0.9925* (*8*)
Shaanxi	1.0326 (4)	1.0129 (15)	*0.9807* (*23*)
Shandong	*0.9888* (*18*)	1.0383 (8)	*0.9865* (*14*)
Shanghai	*0.9883* (*19*)	*0.9733* (*29*)	*0.986* (*15*)
Shanxi	1.0028 (10)	1.0041 (22)	1.0028 (4)
Sichuan	*0.9982* (*16*)	*0.9848* (*26*)	*0.9768* (*26*)
Tianjin	1.0225 (5)	1.0454 (3)	*0.982* (*20*)
Xinjiang	1.0219 (6)	1.0186 (12)	*0.9905* (*9*)
Yunnan	1.0397 (2)	1.0403 (6)	*0.9825* (*19*)
Zhejiang	1.0036 (9)	1.0318 (9)	*0.9857* (*16*)
East China	*0.9698*	1.0051	0.9861
Central of China	*0.9616*	1.0058	*0.9721*
Southern China	*0.9727*	1.0107	*0.9854*
North China	1.0063	1.0253	1.0015
Northeast China	*0.9893*	1.0093	*0.9772*
Northwestern District of China	1.0041	1.0143	*0.9843*
Southwest of China	1.0265	1.0243	*0.9975*
Average	*0.9906*	1.0136	*0.9875*

Note: The numbers in parentheses represent the order and the italics are ML index <1.

forestry output value have declined. It can be seen from the average ML index of all regions in China that values are >1 when only carbon sinks are considered. On the other hand, values are <1 when forestry output value is considered. The static eco-efficiency is lower than economic efficiency but the ecological dynamic changes have an upward trend. Therefore, it played an active role in promoting the productivity of carbon sinks in regions where policies such as afforestation and returning of farmland to forests are vigorously implemented.

6.3. Impact of uncontrollable variables

The second stage of three-stage DEA model adjusts the outputs of forest carbon sinks and output value by introducing environmental variables. All decision-making units were adjusted to the same operating conditions and the change of results from the first stage to the third stage can be compared and analyzed. When carbon sinks and carbon emissions of all the DMUs were adjusted to the most favorable and unfavorable environmental conditions in the second stage. The ML index is greater than it in the first stage. The same rules exist for the results of adjusted forestry output value and carbon emission. It indicates that productivity is improved after eliminating the effects of the uncontrollable variables, so that environmental variables would affect productivity.

The dependent variables in the second stage are slack outputs. If an independent variable has a positive sign, it means that it will increase the expected output slack as the variable increases, which will reduce total factor productivity and vice versa. Harvest has a positive relation with carbon sinks slack and has a negative impact on carbon emissions slack. As a result, it will reduce regional carbon sinks and carbon

Table 4
Regression results of the fixed-effect stochastic frontier models.

Independent variable	Dependent variable	
	Carbon sink slacks	Carbon emissions slacks
HAR	0.1835***	−1.7766
RFDP	−10.1767***	88.6223***
FC	−0.1257***	−0.0297***
RD	−0.00095***	0.0046
λ	2.46e+08***	65.9142

* Significant on 10%.
** Significant on 5%.
*** Significant on 1%.

Table 5
Regression results of the fixed-effect stochastic frontier models.

Independent variable	Dependent variable	
	Forestry output value slacks	Carbon emissions slacks
LUS	0.0039***	0.6189***
OVS	−0.000223***	−0.0457
EUS	−0.000822***	3.1452***
PGI	−2.8178***	560.817**
λ	1.19e+11***	66.7809

* Significant on 10%.
** Significant on 5%.
*** Significant on 1%.

Table 6
The Malmquist–Luenberger index after outputs adjusted.

Region	Case 1		Case 2	
	Luckiest	Unluckiest	Luckiest	Unluckiest
Anhui	*0.9917* (*26*)	*0.9947* (*24*)	1.0052 (15)	*0.9963* (*22*)
Beijing	1.1551 (13)	1.0348 (2)	1.2897 (1)	1.029 (3)
Chongqing	1.3822 (5)	1.0525 (1)	1.1205 (4)	1.0456 (1)
Fujian	*0.9754* (*29*)	1.0001 (17)	1.0901 (5)	1.0033 (11)
Gansu	1.1576 (12)	1.0083 (11)	*0.9827* (*22*)	*0.9954* (*23*)
Guangdong	1.0818 (17)	*0.9892* (*28*)	*0.9469* (*27*)	*0.988* (*26*)
Guangxi	*0.9272* (*30*)	*0.993* (*26*)	*0.8061* (*30*)	*0.9919* (*25*)
Guizhou	2.146 (1)	1.0062 (12)	1.1934 (2)	1.0057 (9)
Hainan	1.3095 (7)	*0.9953* (*22*)	*0.9852* (*21*)	*0.9965* (*21*)
Hebei	1.211 (9)	1.0061 (13)	1.0214 (11)	1.0028 (12)
Heilongjiang	*0.9843* (*27*)	*0.9973* (*19*)	*0.9898* (*19*)	*0.9982* (*16*)
Henan	1.164 (11)	*0.9936* (*25*)	1.0503 (9)	*0.9975* (*18*)
Hubei	1.0807 (18)	1.0253 (4)	1.081 (7)	1.0106 (6)
Hunan	*0.9758* (*28*)	*0.9719* (*30*)	*0.9799* (*23*)	*0.9833* (*28*)
Inner Mongolia	1.0207 (23)	1.02 (6)	1.0214 (11)	1.0004 (15)
Jiangsu	1.0414 (21)	*0.9963* (*21*)	1.1713 (3)	*0.9942* (*24*)
Jiangxi	*0.9953* (*25*)	*0.9965* (*20*)	*0.927* (*29*)	*0.9966* (*20*)
Jilin	1.1179 (15)	1.0111 (10)	1.0153 (13)	1.0018 (13)
Liaoning	1.1524 (14)	1.0219 (5)	*0.9951* (*17*)	1.0081 (8)
Ningxia	1.4965 (4)	*0.9854* (*29*)	*0.9953* (*16*)	*0.9517* (*30*)
Qinghai	1.3364 (6)	1.0116 (9)	*0.9544* (*25*)	1.019 (4)
Shaanxi	1.1953 (10)	*0.9983* (*18*)	1.0514 (8)	*0.9978* (*17*)
Shandong	1.0442 (20)	*0.992* (*27*)	*0.9722* (*24*)	*0.9817* (*29*)
Shanghai	1.9159 (2)	1.0016 (16)	*0.9297* (*28*)	*0.9972* (*19*)
Shanxi	1.0165 (24)	1.006 (14)	*0.9916* (*18*)	1.0041 (10)
Sichuan	1.1016 (16)	*0.9952* (*23*)	*0.9512* (*26*)	*0.9861* (*27*)
Tianjin	1.7534 (3)	1.0146 (8)	*0.9859* (*20*)	1.0312 (2)
Xinjiang	1.2112 (8)	1.0196 (7)	1.0874 (6)	1.0143 (5)
Yunnan	1.0331 (22)	1.0343 (3)	1.0289 (10)	1.0093 (7)
Zhejiang	1.0454 (19)	1.0029 (15)	1.0054 (14)	1.0012 (14)
East China	1.1442	*0.9977*	1.0144	*0.9958*
Central of China	1.0735	*0.9969*	1.0370	*0.9971*
Southern China	1.1062	*0.9925*	*0.9127*	*0.9921*
North China	1.2313	1.0163	1.0620	1.0135
Northeast China	1.0849	1.0101	1.0001	1.0027
Northwestern District of China	1.2794	1.0046	1.0142	*0.9956*
Southwest of China	1.4157	1.0220	1.0735	1.0117
Average	1.2007	1.0059	1.0209	1.0013

Note: The numbers in parentheses represent the order and the italics are Malmquist–Luenberger index <1. Outputs adjusted are based on the outputs slacks which are calculated in the second stage of the three-stage DEA method. Case 1 is the adjustment of carbon sinks and carbon emissions while case 2 adjusts the forestry output value and carbon emissions. But the variables are different in two cases that are used to adjust the outputs. Luckiest is the expected outputs are adjusted to the highest level and unexpected outputs are reduced to the lowest. And unluckiest is that the expected and unexpected outputs adjusted are contrary to that of the luckiest.

emissions while making it impossible to determine the total factor productivity of forest carbon sinks. The increase in harvest will reduce carbon emissions mainly because wood is an important source of biomass energy. Biomass energy is a kind of clean energy, and the use of wood will reduce carbon emissions (Pingoud et al., 2018). The impact of the rate of forest disease prevention on carbon sinks slack is negative, while the impact on carbon emissions slack is positive. Therefore, forest carbon sinks and carbon emissions will increase resulting in uncertainty in the productivity of forest carbon sinks. The impact of forestry research and development on the total factor productivity of forest carbon sinks is the same as that of the rate of forest disease prevention. However, the rate of forest disease prevention has a greater impact on productivity. The coefficient of forest coverage is negative, thus its increment will lead to a decrease in the expected output slack. This will make forest coverage have a significant positive effect on total factor productivity. Increasing forest coverage can effectively promote carbon sinks (Lubowski et al., 2006; Rokityanskiy et al., 2007; Newell, 2000; Adetoye et al., 2018).

In the regression analysis of forestry output value, the ratio of cultivated area to forest area has a positive effect on the two outputs slacks. Therefore, its role in the total factor productivity of forestry is negative. Forestry output value is relatively lower with a larger area of cultivated land and carbon emissions will be high. This can reduce total factor productivity. Output value structure has negative effects on forest output value slack and carbon emissions slack, and plays a key role in promoting the total factor productivity of forestry. The large output value of the primary industry of forestry, which is mainly the production of wood will increase total output value and reduce carbon emissions. As a result, it can reduce carbon emissions and has a similar role as harvest. Energy use structure (the proportion of coal used) has a negative effect on output value slack and has a positive effect on carbon emissions slack. Thus, it has an uncertain effect on the productivity of forestry carbon sinks. If the proportion of coal used is large, it would increase carbon emissions and if the cost is lower than other energy sources, it would increase forestry output value. The effect of governance investment intensity is the same as that of energy use structure. Therefore, in order to increase total factor productivity of carbon sinks, regional carbon sink policies can be formulated by increasing afforestation rate, afforestation area, and returning farmland to forests.

7. Conclusions

Based on the results of the static efficiency and dynamic trends of forestry outputs, and the analysis of the time series and regional differences, forest carbon sinks policies should be adjusted according to local conditions. Output efficiency is stabilized continuously in areas where the level of carbon sinks and its efficiency are high. The strategies for these regions are to exert their advantages of forest resources and actively implement afforestation for the protection of regional ecology. For areas with abundant forest carbon sinks and low efficiency, the advantages of

abundant carbon sink resources should be used to improve the efficiency of forestry output by introducing technologies and improving forest management. All provinces and cities should comprehensively consider the economic and ecological benefits in the development of forest carbon sinks, and allocate resources with consideration of forest management, investment, and technology. At the same time, it can be seen that the decline in forest harvesting and timber production can increase the amount of forest carbon sinks which play a key role in reducing carbon dioxide. Wood is an important biomass and clean energy source and increasing its usage can reduce carbon emissions. Therefore, its impact on the efficiency of forestry is uncertain. Determining the relationship between harvesting volume and the amount of carbon sinks in China will be an important area for further study.

Acknowledgements

The paper is supported by Report Series from Ministry of Education of China (No. 10JBG013) and China National Social Science Fund (No. 17AZD013).

References

Adams, R.M., Adams, D.M., Callaway, J.M., Chang, C.-C., McCarl, B.A., 1993. Sequestering carbon on agricultural land: social cost and impacts on timber markets. Contemp. Policy Issues 11 (1), 76. https://doi.org/10.1108/17506200710779521.

Adetoye, A.M., Okojie, L.O., Akerele, D., 2018. Forest carbon sequestration supply function for African countries: an econometric modelling approach. Forest Policy Econ. 90 (September 2016), 59–66. https://doi.org/10.1016/j.forpol.2018.01.007.

Bai-Chen, X., Ying, F., Qian-Qian, Q., 2012. Does generation form influence environmental efficiency performance? An analysis of China's power system. Appl. Energy 96, 261–271. https://doi.org/10.1016/j.apenergy.2011.11.011.

Chen, S., 2015. The evaluation indicator of ecological development transition in China's regional economy. Ecol. Indic. 51, 42–52. https://doi.org/10.1016/j.ecolind.2014.08.011.

Chung, Y.H., Färe, R., Grosskopf, S., 1997. Productivity and undesirable outputs: a directional distance function approach. J. Environ. Manag. 51 (3), 229–240. https://doi.org/10.1006/jema.1997.0146.

Comin, D., 2008. Total factor productivity. The New Palgrave Dictionary of Economics. August, pp. 1088–1092. https://doi.org/10.1057/9781137336583.1849.

Dakpo, K.H., Jeanneaux, P., Latruffe, L., 2016. Modelling pollution-generating technologies in performance benchmarking: recent developments, limits and future prospects in the nonparametric framework. Eur. J. Oper. Res. 250 (2), 347–359. https://doi.org/10.1016/j.ejor.2015.07.024.

Deng, S., Shi, Y., Jin, Y., Wang, L., 2011. A GIS-based approach for quantifying and mapping carbon sink and stock values of forest ecosystem: a case study. Energy Procedia 5, 1535–1545. https://doi.org/10.1016/j.egypro.2011.03.263.

Dudek, D.J., LeBlanc, A., 1990. Offsetting new CO_2 emissions: a rational first greenhouse policy step. Contemp. Econ. Policy 8 (3), 29–42. https://doi.org/10.1111/j.1465-7287.1990.tb00642.x.

Fang, C.Y., Hu, J.L., Lou, T.K., 2013. Environment-adjusted total-factor energy efficiency of Taiwan's service sectors. Energy Policy 63, 1160–1168. https://doi.org/10.1016/j.enpol.2013.07.124.

Färe, R., Grosskopf, S., 2004. Modeling undesirable factors in efficiency evaluation: comment. Eur. J. Oper. Res. 157 (1), 242–245. https://doi.org/10.1016/S0377-2217(03)00191-7.

Feng, C., Wang, M., 2017. Analysis of energy efficiency and energy savings potential in China's provincial industrial sectors. J. Clean. Prod. 164, 1531–1541. https://doi.org/10.1016/j.jclepro.2017.07.081.

Feng, C., Wang, M., Zhang, Y., Liu, G.C., 2018. Decomposition of energy efficiency and energy-saving potential in China: a three-hierarchy meta-frontier approach. J. Clean. Prod. 176, 1054–1064. https://doi.org/10.1016/j.jclepro.2017.11.231.

Fried, H.O., Lovell, C.A.K., Schmidt, S.S., Yaisawarng, S., 2002. Accounting for environmental effects and statistical noise in Data Envelopment Analysis. J. Prod. Anal. 17 (1–2), 157–174. https://doi.org/10.1023/A:1013548723393.

Greene, W., 2005. Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. J. Econ. 126 (2), 269–303. https://doi.org/10.1016/j.jeconom.2004.05.003.

Gren, I.M., Zeleke, A.A., 2016. Policy design for forest carbon sequestration: a review of the literature. Forest Policy Econ. 70, 128–136. https://doi.org/10.1016/j.forpol.2016.06.008.

Gu, Fengxue, Zhang, Yuandong, Huang, Mei, Tao, Bo, Yan, Huimin, Guo, Rui, et al., 2015. Nitrogen deposition and its effect on carbon storage in chinese forests during 1981–2010. Atmos. Environ. 123 (123), 171–179. https://doi.org/10.1016/j.atmosenv.2015.10.081.

Guo, J., Gong, P., 2017. The potential and cost of increasing forest carbon sequestration in Sweden. J. For. Econ. 29 (Part B), 78–86. https://doi.org/10.1016/j.jfe.2017.09.001.

Hadden, D., Grelle, A., 2016. Changing temperature response of respiration turns boreal forest from carbon sink into carbon source. Agric. For. Meteorol. 223, 30–38. https://doi.org/10.1016/j.agrformet.2016.03.020.

Hoel, M., Sletten, T.M., 2016. Climate and forests: the tradeoff between forests as a source for producing bioenergy and as a carbon sink. Resour. Energy Econ. 43. https://doi.org/10.1016/j.reseneeco.2015.11.005 Elsevier B.V..

Hulten, C.R., 2001. Total factor productivity: a short biography. New Developments in Productivity Analysis. vol. I. https://doi.org/10.1080/09535310701571828.

Koponen, K., Soimakallio, S., Kline, K.L., Cowie, A., Brandão, M., 2018. Quantifying the climate effects of bioenergy – Choice of reference system. Renew. Sust. Energ. Rev. 81, 2271–2280. https://doi.org/10.1016/j.rser.2017.05.292.

Li, K., Lin, B., 2016. Impact of energy conservation policies on the green productivity in China's manufacturing sector: evidence from a three-stage DEA model. Appl. Energy 168, 351–363. https://doi.org/10.1016/j.apenergy.2016.01.104.

Lin, B., Du, K., 2013. Technology gap and China's regional energy efficiency: A parametric metafrontier approach. Energy Econ. 40, 529–536. https://doi.org/10.1016/j.eneco.2013.08.013.

Lin, B., Du, K., 2015. Modeling the dynamics of carbon emission performance in China: A parametric Malmquist index approach. Energy Econ. 49, 550–557. https://doi.org/10.1016/j.eneco.2015.03.028.

Lubowski, R.N., Plantinga, A.J., Stavins, R.N., 2006. Land-use change and carbon sinks: econometric estimation of the carbon sequestration supply function. J. Environ. Econ. Manag. 51 (2), 135–152. https://doi.org/10.1016/j.jeem.2005.08.001.

Makkonen, M., Huttunen, S., Primmer, E., Repo, A., Hildén, M., 2015. Policy coherence in climate change mitigation: an ecosystem service approach to forests as carbon sinks and bioenergy sources. Forest Policy Econ. 50, 153–162. https://doi.org/10.1016/j.forpol.2014.09.003.

Mardani, A., Zavadskas, E.K., Streimikiene, D., Jusoh, A., Khoshnoudi, M., 2017. A comprehensive review of data envelopment analysis (DEA) approach in energy efficiency. Renew. Sust. Energ. Rev. 70 (May 2016), 1298–1322. https://doi.org/10.1016/j.rser.2016.12.030.

Newell, R.G., 2000. Climate change and forest sinks: factors affecting the and the Kyoto protocol to the United Nations framework convention on climate change w 37 x establishes the principle that carbon sequestration can be used by. Environ. Econ. Manag. 40, 211–235 (doi:10.1006rjeem.1999.1120).

Niles, J.O., Brown, S., Pretty, J., Ball, A.S., Fay, J., 2002. Potential carbon mitigation and income in developing countries from changes in use and management of agricultural and forest lands. Philos. Trans. R. Soc. A Math. Phys. Eng. Sci. 360 (1797), 1621–1639. https://doi.org/10.1098/rsta.2002.1023.

O'Mara, F.P., 2012. The role of grasslands in food security and climate change. Ann. Bot. 110 (6), 1263–1270. https://doi.org/10.1093/aob/mcs209.

Pingoud, K., Ekholm, T., Soimakallio, S., Helin, T., 2016. Carbon balance indicator for forest bioenergy scenarios. GCB Bioenergy 8 (1), 171–182. https://doi.org/10.1111/gcbb.12253.

Pingoud, K., Ekholm, T., Sievänen, R., Huuskonen, S., Hynynen, J., 2018. Trade-offs between forest carbon stocks and harvests in a steady state – a multi-criteria analysis. J. Environ. Manag. 210, 96–103. https://doi.org/10.1016/j.jenvman.2017.12.076.

Rajashekar, G., Fararoda, R., Reddy, R.S., Jha, C.S., Ganeshaiah, K.N., Singh, J.S., Dadhwal, V.K., 2018. Spatial distribution of forest biomass carbon (above and below ground) in Indian forests. Ecol. Indic. 85 (November 2017), 742–752. https://doi.org/10.1016/j.ecolind.2017.11.024.

Ray, R., Jana, T.K., 2017. Carbon sequestration by mangrove forest: one approach for managing carbon dioxide emission from coal-based power plant. Atmos. Environ. 171. https://doi.org/10.1016/j.atmosenv.2017.10.019.

Richards, K.R., 2004. A brief overview of carbon sequestration economics and policy. Environ. Manag. 33 (4), 545–558. https://doi.org/10.1007/s00267-003-9111-8.

Rokityanskiy, D., Benítez, P.C., Kraxner, F., McCallum, I., Obersteiner, M., Rametsteiner, E., Yamagata, Y., 2007. Geographically explicit global modeling of land-use change, carbon sequestration, and biomass supply. Technol. Forecast. Soc. Chang. 74 (7), 1057–1082. https://doi.org/10.1016/j.techfore.2006.05.022.

Song, Z., Liu, H., Strömberg, C.A.E., Wang, H., Strong, P.J., Yang, X., Wu, Y., 2018. Contribution of forests to the carbon sink via biologically-mediated silicate weathering: a case study of China. Sci. Total Environ. 615 (92), 1–8. https://doi.org/10.1016/j.scitotenv.2017.09.253.

Sueyoshi, T., Yuan, Y., Goto, M., 2017. A literature study for DEA applied to energy and environment. Energy Econ. 62, 104–124. https://doi.org/10.1016/j.eneco.2016.11.006.

Tone, K., 2011. Slacks-based measure of efficiency. Int. Ser. Oper. Res. Manag. Sci. 164, 195–209. https://doi.org/10.1007/978-1-4419-6151-8_8.

Valade, A., Bellassen, V., Magand, C., Luyssaert, S., 2017. Sustaining the sequestration efficiency of the European forest sector. For. Ecol. Manag. 405 (September), 44–55. https://doi.org/10.1016/j.foreco.2017.09.009.

van Kooten, G.C., Arthur, L.M., Wilson, W.R., 1992. Potential to sequester carbon in Canadian forests: some economic considerations. Can. Publ. Policy Anal. Polit. 18 (2), 127. https://doi.org/10.2307/3551419.

Vass, M.M., Elofsson, K., 2016. Is forest carbon sequestration at the expense of bioenergy and forest products cost-efficient in EU climate policy to 2050? J. For. Econ. 24, 82–105. https://doi.org/10.1016/j.jfe.2016.04.002.

Vlontzos, G., Pardalos, P.M., 2017. Assess and prognosticate greenhouse gas emissions from agricultural production of EU countries, by implementing, DEA Window analysis and artificial neural networks. Renew. Sust. Energ. Rev. 76 (December 2016), 155–162. https://doi.org/10.1016/j.rser.2017.03.054.

Vlontzos, G., Niavis, S., Manos, B., 2014. A DEA approach for estimating the agricultural energy and environmental efficiency of EU countries. Renew. Sust. Energ. Rev. 40, 91–96. https://doi.org/10.1016/j.rser.2014.07.153.

Wang, S., Chen, J.M., Ju, W.M., Feng, X., Chen, M., Chen, P., Yu, G., 2007. Carbon sinks and sources in China's forests during 1901–2001. J. Environ. Manag. 85 (3), 524–537. https://doi.org/10.1016/j.jenvman.2006.09.019.

Williams, C.A., Gu, H., MacLean, R., Masek, J.G., Collatz, G.J., 2016. Disturbance and the carbon balance of US forests: a quantitative review of impacts from harvests, fires,

insects, and droughts. Glob. Planet. Chang. 143, 66–80. https://doi.org/10.1016/j.gloplacha.2016.06.002.

Xu, Q., Yang, R., Dong, Y.X., Liu, Y.X., Qiu, L.R., 2016. The influence of rapid urbanization and land use changes on terrestrial carbon sources/sinks in Guangzhou, China. Ecol. Indic. 70, 304–316. https://doi.org/10.1016/j.ecolind.2016.05.052.

Zhang, C., Liu, H., Bressers, H.T.A., Buchanan, K.S., 2011. Productivity growth and environmental regulations - accounting for undesirable outputs: analysis of China's thirty provincial regions using the Malmquist–Luenberger index. Ecol. Econ. 70 (12), 2369–2379. https://doi.org/10.1016/j.ecolecon.2011.07.019.